NEUZZ: Efficient Fuzzing with Neural Program Learning

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ABSTRACT

Fuzzing has become the de facto standard technique for finding software vulnerabilities. However, even the state-of-the-art fuzzers are not very efficient at finding hard-to-trigger software bugs. Coverageguided evolutionary fuzzers, while fast and scalable, often get stuck at fruitless sequences of random mutations. By contrast, more systematic techniques like symbolic and concolic execution incur significant performance overhead and struggle to scale to larger programs.

We design, implement, and evaluate NEUZZ, an efficient fuzzer that guides the fuzzing input generation process using deep neural networks. NEUZZ efficiently learns a differentiable neural approximation of the target program logic. The differentiability of the surrogate neural program, unlike the original target program, allows us to use efficient optimization techniques like gradient descent to identify promising mutations that are more likely to trigger hard-to-reach code in the target program.

We evaluate Neuzz on 10 popular real-world programs and demonstrate that Neuzz consistently outperforms AFL, a state-of-the-art evolutionary fuzzer, both at finding new bugs and achieving higher edge coverage. In total, Neuzz found 36 previously unknown bugs that AFL failed to find and achieved, on average, $70\times$ more edge coverage than AFL. Our results also demonstrate that Neuzz can achieve average $9\times$ more edge coverage while taking $16\times$ less training time than other learning-enabled fuzzers.

1 INTRODUCTION

In recent years, fuzzing has become one of the most popular techniques for detecting critical security vulnerabilities in large real-world programs [41]. The fuzzing process involves generating random test inputs and executing the target program with these inputs to potentially trigger security vulnerabilities [23]. Due to its simplicity and low performance overhead, fuzzing has been very successful at efficiently finding numerous bugs in large real-world programs, much more so than more sophisticated techniques like symbolic or concolic execution [5, 17, 33].

Most popular fuzzers, such as AFL [41], AFLFast [3], BFF [39], and zzuf [14], use coverage-guided evolutionary algorithms to generate new inputs and maximize their chances of finding new security vulnerabilities. These fuzzers start from a set of seed inputs, apply random mutations to the seeds to generate new test inputs, execute the target program for these test inputs, and only keep the "promising" new inputs for further mutation (*e.g.*, those that achieve new code coverage). To make each run of the target program efficient,

code coverage information is collected by adding lightweight instrumentation to the target program.

However, despite their success, evolutionary fuzzers often tend to get stuck in long sequences of futile mutations without reaching any new code. The key problem is that the evolutionary input generation schemes fail to generalize their observations across different mutations and therefore cannot exploit simple patterns in the target program behavior. Moreover, customizing mutation strategies for different programs manually is a challenging task, as the mutation operators and strategies used in the state-of-the-art evolutionary fuzzers like AFL are more black magic than science [41]. The performance overhead of utilizing more heavyweight context-aware instrumentation or program analysis techniques like taint tracking, symbolic execution, etc., is prohibitive for large real-world programs [36, 41].

Recently, several projects [4, 10, 29] have tried to use different machine learning techniques such as Recurrent Neural Nets (RNNs) and Deep Reinforcement Learning (RL) to make the fuzzing process more efficient. Unfortunately, none of these techniques result in any significant increase in the number of detected bugs or achieved code coverage compared to state-of-the-art evolutionary fuzzers like AFL. Moreover, due to the nature of sequential and stateful modeling used in RNNs and RL, the training and computational overheads of these methods tend to be prohibitively high.

In this paper, we introduce a novel approach using Machine Learning (ML) to efficiently learn customized mutation strategies for effective fuzzing of real-world programs. Unlike the prior ML-based approaches that try to learn the input format of a target program, we learn the logic of the target program itself. Our key observation is that coverage-guided fuzzing can be expressed as an optimization problem whose goal is to select a sequence of mutations that maximize the achieved code coverage for a given target program. However, in general, this is a hard combinatorial optimization problem to solve: the discrete nature of the underlying problem makes it difficult even using heavyweight techniques like Satisfiability Modulo Theory (SMT) solvers.

We sidestep this issue by first learning an approximate continuous and differentiable neural program that can act as a surrogate for the discrete target program. Finding inputs that maximize coverage in the continuous neural program is a numerical optimization problem that, unlike combinatorial optimization, can be solved efficiently using gradient descent. The trade-off is that not all inputs that are predicted to exercise new code by the surrogate neural program will actually result in increased code coverage in the original target program.

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However, as the cost of each run of the target program with a new test input is small, our approach results in significant performance gains as long as the neural program models the target program logic with reasonable accuracy. Our experimental results presented in Section 4 demonstrate that even such incomplete modeling still results in significantly better mutation strategies than existing evolutionary approaches while incurring negligible performance overhead.

We demonstrate that neural programs predicting the control flow edges of the target can be efficiently learned by training Convolutional Neural Networks (CNNs) that predicts which control flow edges will be exercised in the target program by a particular given input. We use CNNs due to their extraordinary capability to learn and automatically extract local structural patterns from raw level inputs without human engineering [20]. Moreover, the feedforward nature of our CNN models result in significantly faster training time than RNN and RL [1]. Once a CNN is trained on some of the test inputs generated by the evolutionary fuzzers, we use scalable gradient-descent-based optimization techniques on the CNN to identify mutation strategies that maximize code coverage in the target program.

We design and implement our technique as part of NEUZZ, a new learning-enabled fuzzer. Our extensive evaluation of 10 real-world programs covering 6 different file formats, (e.g., ELF, PDF, XML, ZIP, TTF, and JPEG) with an average of 47,546 lines of code, shows that NEUZZ consistently outperforms AFL. NEUZZ can achieve on average 70× more edge coverage than AFL given a fixed amount of time budget. Moreover, NEUZZ finds 36 new bugs in the tested program that AFL fails to find. We further demonstrate that NEUZZ outperforms other neural-network-based fuzzers relying on Recurrent Neural Networks (RNNs) [29] by achieving 9× more edge coverage while taking 16× less training time.

Our primary contributions in this paper are as follows.

- We introduce a novel lightweight approach of learning and leveraging a differentiable surrogate neural program for efficient fuzzing of a target program. Our approach uses gradient descent on the differentiable neural program to efficiently find a mutation strategy that maximizes code coverage in the target program.
- We present an efficient way of learning surrogate neural programs using convolutional neural networks (CNNs) that, given a test input, predicts the control flow edges exercised in the target program by the input.
- We design, implement, and evaluate our technique as part of NEUZZ and demonstrate that it achieves, on average, 70× more edge coverage than AFL and finds 36 previously unknown bugs that AFL cannot detect. We also demonstrate that NEUZZ achieves 9× more edge coverage while taking 16× less training time than other neural-network-based fuzzers [29].

The rest of the paper is organized as follows. Section 2 provides an overview of our technique along with a motivating example. Section 3 describes our methodology in detail. We present our experimental results in Section 4 and describe some sample bugs found by NEUZZ in Section 5. Section 6 summarizes the related work and Section 7 concludes the paper.

2 FUZZING AS A LEARNING PROBLEM

Fuzzing is essentially an optimization problem where the goal is to generate a set of new inputs by mutating a set of seed inputs to maximize the number of bugs triggered by the new inputs. However, as it is hard to predict where a bug may appear in a program, maximizing edge-coverage (*i.e.*, the number of new edges covered by test inputs) is often used as a proxy for increasing the chances of finding bugs [41]. Most state-of-the-art fuzzers use evolutionary techniques to generate mutated inputs that increase edge coverage in the target program. However, such approaches often struggle to find inputs that exercise rare and hard-to-reach branches.

2.1 Neural Programs for Fuzzing

In general, finding mutation strategies that maximize edge coverage for an arbitrary target program is a hard combinatorial optimization problem as the logic of the target program is discrete and can be arbitrarily complex. The key insight behind our approach is to approximate the discrete logic of a traditional program by learning a continuous and differentiable neural program. The gradients of such differentiable neural programs can be leveraged to guide the input generation process such that the new inputs maximize the edges coverage in the target program. Note that the actual number of new edges covered by the generated inputs will depend on how accurately the neural program models the logic of the target program. However, as the cost of testing each individual inputs by running the target program is low, the input generation will still be very effective even if the neural program does not perfectly mimic the logic of the target program. Our rationale behind using neural networks to emulate a program's logic is based on the universal approximation theorem [15], i.e., a multi-layer neural network is capable of approximating arbitrary functions given enough training data.

Neural programs. A neural program is essentially a neural network that predicts a target program's behavior by learning a latent representation of the target program's logic. The actual program behavior that a neural program is designed to predict depends on the target usage of the neural program. For example, several recent works have synthesized neural programs from the given input-output samples of a program to accurately predict the program's outputs for new inputs [12, 25, 31]. Such neural programs often define and use more sophisticated differentiable operations than classic layerwise transformations used in traditional neural networks. However, the scalability of these sophisticated models to large and complex programs is not very clear. Moreover, the differentiable operations tend to be task-specific and may not be generalizable.

Neural network architectures. We observe that the neural programs predicting the output of a target program are not a good fit for guiding the fuzzing input generation process, since the task of maximizing cumulative edge coverage for such neural programs is very difficult. By contrast, we design our neural programs such that they predict the control flow edges taken by the target program for a given raw input. Such neural programs allow us to solve the optimization problem of maximizing edge coverage using gradient descent by computing the gradient of different uncovered edges with respect to raw input bytes.

In this paper, we use CNNs [18, 19], a special type of general feedforward fully connected neural net, to model the neural programs.

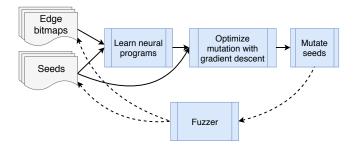


Figure 1: An overview of our approach.

The feed-forward architecture allows highly efficient computation of the gradients and efficient training of such networks [18]. CNNs have also been shown to directly learn from the raw byte-level input without any prior knowledge of the input structure [20] which is crucial for efficient fuzzing. Other neural network architectures like RNNs that include loops and sequentially process the inputs tend to be significantly slower than CNNs both in terms of training and testing. It is worth noting that Rajpal et al. [29] leveraged RNNs to model mutation patterns of inputs and improve fuzzing efficiency by vetoing invalid mutations. Our experimental results demonstrate that NEUZZ achieves $9\times$ more edge coverage while taking $16\times$ less training time than their approach (see Section 4).

Similarly, reinforcement learning (RL) techniques using deep neural networks to model the reward functions [4] also do not seem to be a natural fit for fuzzing. RL-based approaches assume that the environment is relatively stable, *i.e.*, performing the same action will result in somewhat similar rewards. However, coverage-guided fuzzing violates such assumptions, because repeating the same mutation does not increase cumulative branch coverage. Besides, RL is known to be notoriously difficult for its hyperparameter tuning during training [16, 32]. Therefore, we do not consider RL for learning neural programs in this paper.

2.2 Overview of Our Approach

Figure 1 presents a high level overview of our approach. We describe the main design choices below.

Input representation. The input to a neural program can be modeled at various granularities. A fine-grained scheme may treat every input as raw bytes, where each byte encodes one feature with possible values between 0 and 255. By contrast, coarse-grained but higher-level features may leverage domain knowledge about the input structure, such as grammar-based abstract syntax trees [37] or details about the input format (*e.g.*, PDF) [10]. In this work, we use the raw bytes as input features and exploit the CNN's to extract hidden patterns from raw byte-level inputs.

Output representation. Recall that our task is to learn a neural program that can approximate a target program, and then use this neural program to generate inputs that can achieve higher edge coverage. Therefore, we model the output of the neural program to directly predict the edge coverage for a given input. In particular, the output of the neural program is a bit vector representing the covered edges, where each output neuron in the final layer denotes one edge and the output value of the neuron denotes whether the

edge is covered or not (*i.e.*, 1 denotes covered while 0 denotes not covered).

Therefore, the neural program becomes a multi-input and multi-output function mapping the raw bytes of the program input to the corresponding covered edges of the program. Note that we develop an edge merging algorithm (described in Section 3) to avoid the potential blow-ups in the number of output neurons for the large program with many edges.

Sources of training data. We use the test inputs generated by evolutionary fuzzing to train the CNN to learn the logic of the target program. Specifically, we collect a set of test inputs and the corresponding edge coverage information by running evolutionary fuzzers like AFL for a short duration and use them for training the CNN.

2.3 A Motivating Example

We use the code in Listing 1 as a motivating example to elaborate the workflow for NEUZZ using Figure 2. NEUZZ has two main steps: (1) Training an NN to learn the logic of the program under test (Figure 2a). (2) Computing gradient of the model to locate the critical bytes in input and mutate them (Figure 2b) based on the gradient value.

Listing 1: Sample code snippet for demonstrating the workflow of NEUZZ

The simple $\mathbb C$ code snippet shown in Listing 1 demonstrates a general switch-like code pattern which we find is common in real-world programs. In particular, the example code includes a list of non-linear exponential functions (*i.e.*, pow(2, x[4])). It checks each bit of the function output is 1 or not where the function takes as input the fifth byte of program's input (x[4]). If the fifth bit (line 12) is 1, then it enters a buggy code block (marked in **red**).

There are three main challenges we aim to solve in fuzzing this program: (1) how to locate the critical byte to mutate (the fifth byte), (2) how to arrive at the exact perturbation to introduce in the mutation, (3) how to handle the nonlinearity in the code that solver-based techniques (*e.g.*, symbolic execution) often fail to efficiently solve. NEUZZ aims to address these challenges effectively and efficiently in the following way.

Training. Recall that the NN model's input is the input to the original program, and its output is the program control flow edges covered by this input (see Section 2.2). Thus, for a given program, we train NEUZZ with fuzzing inputs and the true corresponding covered edges (see Figure 2a). The training data can be easily collected by running AFL or cheap random fuzzing for a while (*e.g.*, 1 hour or 6 hours in evaluation in Section 4).

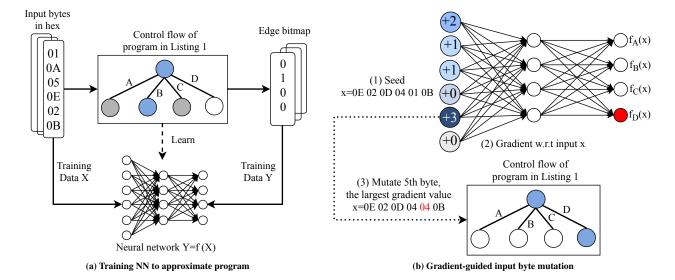


Figure 2: An example NEUZZ workflow to fuzz the program in Listing 1. The left figure shows training the NN $f(\cdot)$ using the training data. The right figure denotes how NEUZZ mutates the seed input based on the gradient computed from the trained NN. This includes three steps, (1) feed the seed input x=0E 02 0D 04 01 0B to the NN. (2) Computing the gradient of the fourth output neuron (note that we can randomly pick other edges to cover), denoted as $f_D(x)$, w.r.t. the input. (3) Mutate the bytes at locations based on gradient value in each input neuron. The darker the color, the larger the gradient value.

Each input neuron in the input layer denotes one byte. The output encodes all edges as a bit vector (*i.e.*, edge bitmap), where each binary bit denotes whether one edge is covered or not. For example, corresponding to Listing 1's control flow, as shown in Figure 2a, say a training input 01 0A 05 0E 02 0B triggers only the second edge of the program: as $\times [4] = 2$ and $2^2 = 4_{10} = 100_2$. Thus, the second entry in the bitmap will be set to 1. Note that we also mark the covered edges in training data with its connecting nodes as gray in Figure 2a. After collecting enough such training data, a neural network (denoted as $f(\cdot)$) is trained to learn to map X to Y. For the ease of exposition, we use three-layer fully connected NN.

Gradient-guided mutation. In the second step (Figure 2b), the seed inputs generated by AFL are fed to the trained NN to compute their gradient. We calculate the location and type of mutation to the seed required to reach an uncovered edge based on this gradient.

For example, for seed input 0E 02 0D 04 01 0B, x [4] =1. Thus, it cannot trigger any edge in the code Listing 1 and the output of each neuron in the final layer is 0¹. Now, a fuzzer would want to mutate the seed to cover another edge, *e.g.*, the fourth edge. NEUZZ resorts to computing the gradient for the guidance. In particular, we compute the gradient of the output $(f_D(x))$ of the fourth edge w.r.t. input x, *i.e.*, $f'_D(x) = \partial f_D(x)/\partial x$, and add the computed gradient value to the input to make the changed input to cover different edges of interest (see Figure 2). In this example, the gradient value to maximize the fourth output neuron is [2, 1, 1, 0, 3, 0]. This gradient provides useful information to answer the three questions mentioned at the beginning of this section:

- 1. Locating critical bytes. The location in the gradient with the greatest value is essentially implied to be the most important input byte to maximizing the output neuron, i.e., the NN thinks this is a critical input location to maximize $f_D(x)$. Here $\times [4]$ has the greatest gradient value, which is consistent with the real program logic.
- 2. Obtaining mutation amount. The gradient value essentially implies the amount of mutation that we should add to the input. In this example, the gradient value of \times [4] is 3, and by adding 3 to the seed value of \times [4] we get 1+3=4. Now as \times [4]=4, we can see that fifth edge (line 15) is covered because $2^{x[4]}=2^4=16_{10}=010000_2$. Note that the gradient computation in practice may not be as accurate as shown in this running example. In that case, we perform an exhaustive search starting by following the direction indicated by the sign of the gradient value [11]. The detailed algorithm of our gradient-guided search is described in Section 3.
- 3. Handling nonlinearity. As the trained NN can approximate any type of operation (including highly nonlinear computations), as long as our training is effective, the resulting gradient can reveal the direction in which input should be mutated to optimize the original goal of covering different edges. Whereas the SMT solver such as z3 cannot efficiently handle this exponential (transcendental) functions.

3 METHODOLOGY

In this section, we describe our methodology in detail and formalize the concepts that relate to the workflow shown in Figure 2. As briefly mentioned in Section 2.3, there are several practical considerations that must be considered in the development of NEUZZ, such as blowup of the number of edges that need to be encoded and mutation based on inaccurate gradient computation. We divide the description

¹As a neuron's output is a continuous value, we set a threshold of 0.5; the output of any neuron greater than this threshold is set to 1 (*i.e.*, the corresponding edge is covered).

of methodology into two parts. The first part formally describes the training process of the NN that maps raw program input to edge coverage, and the underlying algorithm to handle variable input-output length. The second part includes the detail of gradient computation and the algorithm to generate mutations based on the gradient value.

3.1 Neural Program Learning

Let $f: \{0 \times 00, 0 \times 01, ..., 0 \times ff\}^m \to \{0,1\}^n$ denote the NN that takes program inputs as byte sequences with size m and outputs an edge bitmap with size n. Let θ denote the trainable weight parameters of f. Given a set of training samples (X,Y), where X is a set of input bytes and Y represents the corresponding edges covered as a bitmap, the training task of the parametric function $f(x,\theta) = y$ is to look for the parameter $\hat{\theta}$ such that $\hat{\theta} = \arg\min_{\theta} \sum_{x \in X, y \in Y} L(y, f(x,\theta))$ where

 $L(y,f(x,\theta))$ defines the loss function between the output of the NN and the ground truth label $y \in Y$ in the training set. The training task is to find the weight parameters θ of the NN f to minimize the loss, which is defined using a distance metric. In particular, we use binary cross-entropy to compute the distance between the predicted bitmap and the true coverage bitmap. In particular, let y_i and $f_i(x,\theta)$ denote the i-th bit in the output bitmap of ground truth and f's prediction, respectively. Then, the binary cross-entropy between these two is defined as:

$$-\frac{1}{n} \sum_{i=1}^{n} [y_i \cdot log(f_i(x, \theta) + (1 - y_i) \cdot log(1 - f_i(x, \theta))]$$

Training f requires preprocessing the data in a fixed format. For example, we have to fix the length of input to be m and output to be n. However, in practice, the input to a program can vary in length. Moreover, since the number of edges (i.e., control-flow branches) in a program can be enormous, encoding every program edge as a bit in the output can incur a huge performance overhead: there may be groups of edges that are always covered together, or edges that can never be reached. In order to handle variable input length, we fix the length of input to the NN (e.g., m = 10000). This setting allows a balance between efficient training performance and inclusion of extreme cases observed in the training data. While it is possible to have longer inputs, our empirical analysis in Section 4 demonstrates the maximum input length bound still achieves decent results, while modeling longer inputs can lead to potentially worse training time and generation efficiency. For inputs having length shorter than m, we can treat the remaining bytes as an insignificant padding value (i.e., null 0×00), since each input byte can take any value between 0x00 to 0xff.

Output branch merging. Naively, we can use one bit to represent coverage of each edge. However, we observe that the number of edges in the programs tested is too large to do this practically. We thus perform branch merging operation based *only on the knowledge of the training data* to avoid expensive analysis and program instrumentation. Specifically, to reduce the number of dimensions in the output bitmap, we perform following steps: (1) Instead of setting a fixed, sufficiently large dimension as in the input encoding, we only consider the edges that have been activated in the training data. Therefore, unlike AFL, which maintains a fixed-length (65,536-long)

mapping of branches, many of which are spurious and nonexistent in a target program, our encoding intelligently saves space. In fact, it usually results in around only 4,000 dimensions compared to the naively created 65,536 dimensions. (2) We seek to merge edges that are *always* covered together by every training sample, and we use one bit to represent each group. For example, one of the most obvious cases is two nested if branches where the inner if always true given the outer if is satisfied. In this case, the two edges will be merged into one edge.

Admittedly, this encoding based only on the information in training set can potentially miss some edge information that is not present. However, our objective is to provide an efficient, though not necessarily perfectly accurate, guiding strategy. In fact, we have also empirically tried the encoding using the default 65,536 dimensions provided by AFL. Our results indicate that the trained NN behaves in a way far from the real program logic and thus the gradient computed cannot map the mutation to the presence of newly covered edges. Moreover, as there are many spurious edges, nonexistent yet present in the encoding, selecting the right output neuron (that represents an actual program edge) to calculate the gradient becomes impossible.

3.2 Gradient-Guided Mutation

Before elaborating on the mutation strategy, which is based on the neural net's gradient, we first give a formal definition of the gradient, which designates how much each input byte should be changed in order to affect the output of a specific neuron in the final layer of the NN f. This is also known as *input saliency map* [34].

Input saliency based on gradient. The gradients of the output neurons of a DNN f w.r.t. the input are well known in deep learning literature. They have been extensively used both for crafting adversarial examples [11, 28] and visualizing/understanding DNNs [22, 34, 40]. We provide a brief definition here for completeness and refer interested readers to [40] for more details.

Given parametric NN $y = f(\theta, x)$ as defined in Section 3.1, let y_i denote the output of i-th neuron in the final layer of f, which can also be written as $f_i(\theta, x)$. The gradient G of $f_i(\theta, x)$ with respect to input x can be defined as $G = \nabla_x f_i(\theta, x) = \partial y_i/\partial x$. Note that f's gradient w.r.t to θ can be easily computed as training f requires iteratively computing this value for updating θ . Therefore, G can also be easily calculated by just replacing the computation of gradient of θ to x. Note that the dimension of the gradient G is identical to that of the input x, which is a byte sequence in our case.

Dynamic top-k **critical bytes.** After computing the gradient, our next step is to pick the critical bytes to mutate. As shown in Section 2.3, the absolute value of the gradient indicate the saliency of input bytes towards optimizing the selected output neuron f_i , which is equivalent to increasing the possibility of covering that particular edge. Given one seed, we try to iteratively generate a set of mutations. At each iteration, we examine the value of gradient for each byte to determine whether the bute should be mutated. We start with a more selective filter, choosing only a small number k of locations to mutate. The assumption fueling this choice is that achieving new program edge coverage is possible by changing even a few input bytes. Then, as the iterations progress, we aim to be more ambitious in mutating more critical bytes per round in order to cover the case where a large number of bytes together cover an edge. As shown in

Algorithm 1 Gradient-guided mutation

```
Input:
            seed ← initial seed
            iter ← number of iterations
            \mathbf{k} \leftarrow parameter for dynamic top-k critical bytes
            \mathbf{g} \leftarrow computed gradient of seed
1: for i = 1 to iter do
       locations \leftarrow top(g, k^i)
2:
3:
       for m = 1 to 255 do
            for loc ∈ locations do
4:
                 v \leftarrow seed[loc] + m * sign(g[loc])
5:
                 v \leftarrow clip(v, 0, 255)
6:
7:
                 gen_mutate(seed, loc, v)
8:
            for loc \in locations do
                 v \leftarrow seed[loc] - m * sign(g[loc])
9:
```

 $v \leftarrow clip(v, 0, 255)$

gen_mutate(seed, loc, v)

10: 11:

Algorithm 1 line 2, we pick the locations of top k^i in the gradient q. By exponentially growing the number of candidate bytes to mutate, we can easily cover different cases throughout the whole input space. Mutation strategy. As discussed in Section 2.3, in practice, mutating each byte based on the specific gradient value may not be accurate enough to guide the mutation towards covering the edges of interest. In our implementation, we hope to fully exploit the information provided by the gradient about the critical byte location. To this end, we perform the search more exhaustively than just adding a single value around the critical location. Specifically, we adopt the strategy similar to the gradient sign technique introduced in [11]. The sign of the gradient at each input byte indicates the mutation direction. For example, if we want to mutate two bytes 0A and 07, and the sign of gradients for 0A and 07 are negative (-1) and positive respectively, decreasing 0A and increasing 07 is a promising direction to cover the edge of interest.

We iteratively increment or decrement the byte of the critical locations by trying different legal byte values from (1-255). If the sign of the gradient for a mutated byte is 1, then increment the byte value, else we decrement. Line 3 to line 11 in Algorithm 1 demonstrate our mutation strategy. Note that lines 4 through 7 perform gradient ascent which essentially *maximizes* the output of the neuron, while lines 8 through 11 *minimize* the output of neuron, which hopefully can generate mutations to cover other edges by *not* going to this particular edge of the designated neuron of gradient computation.

4 EVALUATION

In this section, we discuss our experimental settings and how we finetune NEUZZ to achieve optimal performance. Next, we evaluate the effectiveness of NEUZZ compared to AFL regarding code coverage, crashes and new bugs found on a variety of real-world programs. We also compare NEUZZ (CNN-based fuzzing) with an existing RNN-based fuzzing tool.

4.1 Experimental Setup

We evaluate NEUZZ on 10 real-world programs in their most updated version. Table 1 provides the summary of the programs. All our

Table 1: Tested programs with total number of lines, time NEUZZ takes to train the model, and baseline coverage achieved by the training data generated by AFL in 1 or 6 hours

Programs		# Lines	NEUZZ	AFL coverage	
Class	Name	# Lines	train (s)	1 hour	6 hour
	readelf -a		114	4,662	5,546
$binutils\hbox{-}2.30$	nm -C	53,457	52	3,484	3,662
ELF	objdump -D	72,955	105	5,236	5,422
Parser	size	52,991	82	2,362	2,532
	strip	56,330	52	5,291	5,563
TTF	harfbuzz-1.7.6	9,853	117	7,425	8,494
JPEG	libjpeg-9c	8,857	52	3,071	3,103
PDF	mupdf-1.12.0	123,562	71	4,404	4,653
XML	libxml2-2.9.7	73,920	160	6,776	6,964
Zip	zlib-1.2.11	1,893	139	996	1,277

measurements were performed on a system running Arch Linux 4.9.48 with an Nvidia GTX 1080 Ti GPU.

Dataset. We run AFL-2.5.2 2 on a single core for an hour to collect data to train our NN model. The resulting corpus generated by AFL is split into training data and testing data by a 5:1 ratio. Our NN model is based on a CNN which requires a fixed input dimension. The program input may be varied length, so we choose a threshold file size 10 KB. Then we remove the few inputs with file size greater than the threshold 10 KB and only keep inputs with file size within 10 KB. We also pad 0×00 byte to the end of every input to ensure they have a fixed length. Before starting fuzzing, we choose an initial seed with size less than 10 KB. The benefit of a proper sized initial seed is that most of the mutations generated by AFL have a consistent file size with initial seed. Thus most of the mutated inputs in AFL result corpus have the file size less than 10 KB, and we can keep most of them in training data. A consistent training dataset can help the NN model to learn underlying rules well.

NN architecture. Our NN model is implemented in Keras-2.1.3 ³ with Tensorflow-1.4.1 4 as a backend. The NN model consists of three 1-dimensional convolution layers and one fully-connected layer. Every layer uses ReLU as its activation function. The kernel size for convolution layers is 9, and the stride length is 3. We also add two dropout layers with 25% disabling rate after convolution layers and fully-connected layer to avoid overfitting. We use sigmoid as the activation function for each neuron's output layer. The NN model is trained for 50 epochs to achieve a promising test accuracy of around 95%. Since our NN model is relatively simple (i.e., 3 CNN layer and 1 FC layers), all 10 programs can finish training within 2 minutes. We also experiment training our NN model with pure CPU computation, an Intel i7-7700 running at 3.6GHz, and the training time is just under 20 minutes. This shows the superior computational efficiency of NEUZZ which can be deployed on a general PC without a dedicated GPU because of small its NN model and proper, compact data representation.

²lcamtuf.coredump.cx/AFL/

³keras.io

⁴www.tensorflow.org

Mutation. We use the mutation algorithm described in Section 3.2 (Algorithm 1) to generate 1 million mutations. We set the parameter i to 10, which generates 5,120 mutated inputs for seed. We randomly choose 100 output neurons representing 100 edges in a program. For every selected edge, we choose two seeds and generate 10,240 mutated inputs to explore the edge condition. Thus, using NEUZZ, for 100 edges we generate just about 1M mutations.

Next, we run AFL with the same initial seed used to generate NN training data until it generates 1 million mutations. AFL implements a global counter to measure how many executions it performs. However, the number of executions is not equal to the number of mutations generated by AFL, because AFL performs multiple executions for a single mutation to determine additional information used in its genetic mutation algorithm. To measure the exact number of mutations generated by AFL, we add a counter to AFL's implementation. The modified AFL can thus fuzz a program and exit after it generates 1 million mutations.

Finally, we run the test program separately with the two sets of mutated inputs generated by NEUZZ and AFL respectively and compare the code coverage, the number of bugs and crashes found. Note that we only report the additional code that is covered by the mutated inputs without including the coverage information from the initial seed generation process.

Comparison. Since NEUZZ is essentially a mutation generator, we evaluate NEUZZ w.r.t. AFL by comparing the achieved code coverage, crashes, and bugs found by the two techniques under the same number of mutations. The overhead of mutation generation for NEUZZ is negligible. It only requires a small number of gradient computations on a simple NN model to generate a large number of mutations. In particular, for generating 1M mutations, NEUZZ needs to compute gradients for only 100 times, which can finish in 10 seconds on average. On the other hand, AFL implements a genetic algorithm to generate mutation with an additional overhead of checking edge coverage for every mutation, which is in general time-consuming. To focus on the quality of the mutations generated by the two techniques, we ignore the overhead of the mutation generation process of AFL. The other overhead of seed generation and program execution are the same for NEUZZ and AFL. To further amortize NEUZZ's overhead, mutation generation process can be offline, while AFL mutation generation is an on-the-fly process. Thus, NEUZZ can generate mutations from the surrogate neural program in parallel with the target program execution, which is not possible for AFL.

4.2 Model Parameter Selection

The success of NEUZZ depends on the choices of different parameters in training the models and generating mutations. For example, the mutation algorithm would choose k^i (see Algorithm 1 line 1) number of most critical bytes to mutate for every initial seed. A larger k^i indicates mutating more bytes per mutated seed. Another example is the choice of hyperparameters in the CNN model we use, such as the number of layers and the number of kernels in each convolutional layers. This section investigates the effect of these parameter choices.

We choose k = 2 from the dynamic top-k described in Section 3.2 and show the coverage achieved by three iterations alone

Table 2: Training time comparison of NEUZZ (CNN fuzzer) and RNN fuzzer

Programs	1 hou	corpus	6 hour corpus		
Tiograms	CNN	RNN	CNN	RNN	
readelf -a	114s	2,224s	168s	2,936s	
libjpeg	52s	1,028s	73s	1,216s	
libxml	160s	2,642s	217s	2,930s	
mupdf	71s	848s	94s	1,312s	

Table 3: Code coverage achieved by mutations generated in different iterations (Algorithm 1 line 1), the numbers in bold indicate the highest values for each program

Programs		Iteration i	
riograms	7	10	11
readelf -a	1,834	2,378	1,612
libjpeg	283	142	241
libxml	178	273	191
mupdf	154	120	126

(i = 7, 10, 11 in Algorithm 1 line 1) with setting the total 1 million mutations for each iteration. We compare their edge coverage on four programs, namely readelf, libjpeg, libxml, and mupdf. The aim of this evaluation is to explore the empirically optimal parameters in terms of how many bytes per mutated seed. The result are summarized in Table 3. For all four programs, we observe that smaller number of bytes per mutation can lead to more code coverage. The largest i = 11, which means we mutate $2^{11} = 2048$ bytes in each mutation, achieves the least code coverage for all four programs. This result is potentially due to lines 4 and 8 in Algorithm 1 "wasting time" on a single seed without trying other more promising seeds given a fixed number of allowed mutations. However, the optimal number of mutation bytes for the four programs examined does vary. For readelf and libxml, the optimal number of mutation bytes is $2^{10} = 1024$. For libjpeg and mupdf, the optimal iteration number is $2^7 = 128$. Since the code coverage difference between i = 7 and i = 10 is not large, we choose i = 10for our experiments.

We further determine the effect of varying width and depth in the CNN model on code coverage on the same four programs as described above. Specifically, we compare the architecture of 3 layers, 6 layers and 128 kernels, with 256 kernels per layer. For every tested program, we use same training data to train four different CNN models and generate 1M mutations to test the coverage achieved. The results are summarized in Table 4. For all four programs, we find 3 CNN layers model have better code coverage than 6 CNN layers model. We think this is because the 3-layer model is sufficiently complex to learn program logic. The larger model (*i.e.*, 6 layers) is much harder to train and also tends to overfit.

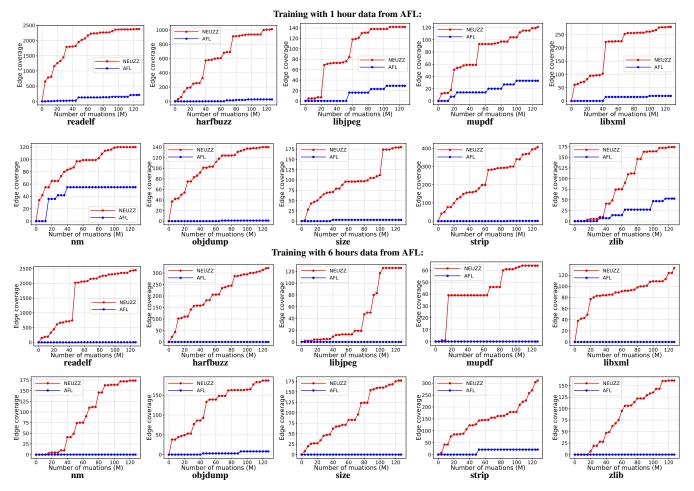


Figure 3: The edge coverage of 1M mutations generated by AFL and NEUZZ, after training with 1 and 6 hour(s) data, respectively.

Table 4: Comparison of the effect of different NN models. n denotes the number of kernels in every convolution layer

Dragrama	3 CNN	layers	6 CNN layers		
Programs	n=128	n=256	n=128	n=256	
readelf -a	1,971	2,378	411	298	
libjpeg	149	142	88	92	
libxml	316	273	206	193	
mupdf	264	121	166	162	

4.3 Results

RQ1. Can NEUZZ explore more code than AFL?

To investigate this question, we compare the fuzzers in two settings: (1) under fixed constrained mutation budget, and (2) with more resources.

Fixed mutation budget. First, we evaluate the efficiency of NEUZZ and AFL on 1 million mutations and compare the edge and line coverage obtained by the two techniques. We collect the edge coverage information from AFL edge coverage report; line coverage

is measured using gcov⁵. The results are summarized in Table 5a. We see that for both edge and line coverages, NEUZZ significantly outperforms AFL.

For all the programs tested, NEUZZ achieves significantly more new code coverage than AFL. In terms of new edges, NEUZZ finds 2.1 to 407 times more new edges than AFL, where 6 out of 10 programs under test achieve more than 10 times new edge coverage. Similarly, in terms of new lines, NEUZZ finds 28 to 1229 more new lines than AFL. Note that, in general, line coverage exceeds edge coverage. However, since the Table only reports new code coverage (*i.e.*, not including the coverage information achieved while generating the training corpus), the number of new lines covered can be less than the number of new edges.

NEUZZ is quite effective in finding new edges. For projects strip, objdump, size, and libxml, NEUZZ achieved the highest edge coverage w.r.t. AFL—407, 140, 60, and 14 times more than AFL respectively. For these programs, AFL finds very few new edges. This shows that most of the mutations generated by AFL fail to explore new edge conditions. These gains show the power

⁵https://gcc.gnu.org/onlinedocs/gcc/Gcov.html

Table 5: Code coverage of 1M mutations generated by NEUZZ and AFL

(a) New code coverage while running AFL for 1 hour to generate the training data

	Line cov	erage	Edge coverage		
Programs	NEUZZ	AFL	NEUZZ	AFL	
readelf -a	1,412	183	2,378	213	
nm -C	40	0	120	56	
objdump -D	82	0	140	1	
size	67	0	180	3	
strip	75	0	407	1	
libjpeg	160	19	142	28	
libxml	204	5	273	19	
mupdf	28	0	121	32	
zlib	138	5	174	53	
harfbuzz	284	0	1,014	27	

of NEUZZ to locate critical bytes and mutate them based on the gradient to find the new edges.

NEUZZ can efficiently find new edges for large systems as well. We observe that NEUZZ achieves the highest edge coverage for readelf, harfbuzz, strip, and libxml—2378, 1014, 407, 273 respectively - compare to 213, 27, 1, 19 new edges covered by AFL. Interestingly, all these programs are large programs with more than 10K lines of code. This disparity may result because large programs have more possible edges to explore than small programs. These results confirm that NEUZZ can scale well, perhaps better than AFL, for large programs.

Although the above results show that NEUZZ can find new code more efficiently than AFL under a fixed resource budget, it may be possible that given more resources, AFL can eventually match NEUZZ's coverage performance. Thus we check: can AFL match NEUZZ with more resources?

Allocating more resources. Here, we run AFL long enough so that it no longer is able to cover new code branches. In particular, we run AFL for 6 hours - at this point, AFL either stagnates completely (in 7/10 programs), unable to discover additional coverage, or finds new branches very slowly (as is the case for three of the ten programs tested).

We then use the corpus generated by AFL after a 6 hour run as data to train NEUZZ and generate 1 million mutations. We also use the same 6 hour corpus as the initial seed for AFL and let it generate 1 million mutations further. We then compare code coverage, crashes, and bugs found using these two mutation corpora. The result is summarized in Table 5b.

For all ten projects, NEUZZ outperforms AFL significantly. AFL can only find new code on 3 out of 10 programs. The decrease of AFL's code coverage is somewhat expected as AFL is known to suffer from this "stuck problem". Most of the easy edges are covered within 6 hours of fuzzing, so AFL encounters difficulty in coming across new edges. For all programs tested, NEUZZ achieves significantly higher new code coverage (both edge and line). In terms of edge coverage, NEUZZ finds 2447, 172, 179, 177, 290, 126, 133, 63, 161, 322 more new edges than AFL. In terms of line coverage,

(b) New code coverage while running AFL for 6 hours to generate the training data $\,$

Drograms	Line cov	erage	Edge coverage		
Programs	NEUZZ	AFL	Neuzz	AFL	
readelf -a	1,569 0		2,451	4	
nm -C	145	0	174	0	
objdump -D	58	2	187	8	
size	33	0	177	0	
strip	71	0	311	21	
libjpeg	294	0	126	0	
libxml	87	0	133	0	
mupdf	15	0	63	0	
zlib	97	0	161	0	
harfbuzz	52	0	322	0	

NEUZZ finds 1569, 145, 56, 33, 71, 294, 87, 15, 97, 52 more new lines

Compared with other solutions [3] [36] that try to solve the stuck problem, NEUZZ has the advantage of little training overhead and zero overhead in execution. The training time is also shown in Table 1.

To further illustrate the efficiency of NEUZZ vs AFL, we plot edge coverage vs number of mutations generated by both fuzzers in Fig 3. For NEUZZ trained with 1 hour data, NEUZZ consistently finds more edges than AFL by 70 times, on average. For NEUZZ trained with 6 hours data, NEUZZ still consistently outperforms AFL on all 10 programs. We observe that AFL got stuck on 6 hours data because it becomes more difficult to find new edges after long hours of running. In contrast, NEUZZ is not affected by the larger training data and still finds significantly more edges. These results show NEUZZ can find substantially more edges that AFL fails to find.

Result 1: Neuzz can achieve significantly higher edge coverage (70 times, on average) than AFL. Even with increased time budget, AFL is unable to match Neuzz.

RQ2. Does NEUZZ find more crashes and bugs than AFL?

The ability to find bugs is an important metric in evaluating a fuzzer. We compare the total number of bugs and crashes found by NEUZZ and AFL on 1 million mutations over 6 hours of training data. There are four different types of bugs found by NEUZZ and AFL: out-of-memory, memory leak, crash, and integer overflow. To detect memory bugs that would not necessarily cause a crash, we compile program binaries with address sanitizer⁶. We measure the unique memory bugs found by comparing the stack traces reported by the address sanitizer. For crashes that do not cause a bug report to be generated by the address sanitizer, we examine the execution trace.

⁶https://github.com/google/sanitizers

Table 6: Number of bugs found by AFL and NEUZZ. We use x/y to denote the number of bugs found by NEUZZ and AFL, respectively, when they differ

Programs	Mem	Out	Interger	Crash	NEUZZ	AFL
	leak	mem	overflow	Crasii	Total	Total
readelf	10/4	0	0	6/0	16	4
nm	0	8/8	0	0	8	8
objdump	2/0	6/6	0	0	8	6
size	0	5/3	0	0	5	3
strip	5/1	14/6	7/0	0	26	7
libjpeg	0	1/0	0	0	1	0
libxml	0	0	0	0	0	0
mupdf	0	0	0	0	0	0
zlib	0	0	0	0	0	0
harfbuzz	0	0	0	0	0	0

The integer overflow bug is found by manually analyzing the inputs that trigger an infinite loop. We further verify integer overflow bugs using the undefined behavior sanitizer⁷. The results are summarized in Table 6.

NEUZZ finds all the 4 types of bugs across 6 programs, while AFL finds only 2 types of bugs in 5 programs. The two unique types of bugs found by NEUZZ are logic bugs: one induces an infinite loop in strip and the other is a crash-inducing bug in readelf. We will discuss them in detail in Section 5. As for memory bugs reported by the address sanitizer, NEUZZ finds memory leaks in 3 programs and out-of-memory bugs in 5 programs, while AFL finds memory leaks in 2 programs and out-of-memory bugs in 4 programs. NEUZZ is able to find all the memory bugs that AFL finds along with additional memory leaks in 3 programs and out-of-memory bugs in 2 programs. NEUZZ further finds 6 crashes in readelf and 7 integer overflows in Strip. In total, NEUZZ finds 64 bugs while AFL finds 28 bugs.

Result 2: Neuzz found 36 previously unknown bugs in 6 different programs that AFL could not find.

RQ3. How does NEUZZ compare against am RNN-based fuzzer?

Existing work in NN-based fuzzing has shown that RNNs can be used to learn mutation patterns from past fuzzing experience to guide future mutations [29]. These works use RNN models to learn mutation patterns (composed of critical bytes) from a large number of mutated inputs generated by AFL. Then, they use the mutation patterns to build a filter to AFL, which only allow mutations on critical bytes to pass, vetoing all other non-critical byte mutations. We choose the 4 programs used in the previous work to evaluate the performance of NEUZZ and the RNN-based fuzzer after 1 million mutations. To evaluate the efficiency and the ability to find the new code, we perform the comparison on both a 1 hour corpus and a 6 hour corpus as training data, as discussed previously. We

train the two NN models with same training data, let the two NN-based fuzzers run to generate 1 million mutations, then compare the new code coverage achieved by the two methods. To simplify the evaluation, we only measure the edge coverage. We also add new code coverage of AFL as a baseline.

The result is summarized in Table 7. For all the four programs, NEUZZ significantly outperforms the RNN-based fuzzer on both 1 hour and 6 hours corpora. With the 1-hour corpus, NEUZZ achieves 11.1, 6.8, 7.2, 1.5 times more new edge that the RNN-based fuzzer across the 4 programs. With the 6-hour corpus, NEUZZ achieves 18.7, 126, 8.9 times more new edges than the RNN-based fuzzer on 3 programs. For mupdf, the RNN-based fuzzer fails to find any new edges, while NEUZZ finds 63 new edges.

Interestingly, the RNN-based fuzzer achieves 2 times more edge coverage, on average, than AFL on programs libxml and mupdf on 1-hour corpus, but it does not increase coverage on 6 hours corpus, a "stuck pattern" that is similar to the one AFL exhibits. This is because the RNN-based fuzzer is essentially an AFL with additional mutation filters; it highly relies on AFL's mutation strategy. We also observe that the RNN-based fuzzer vetoes 50% of the mutations generated by original AFL on average, so the new code coverage of 1M mutations from RNN-based fuzzer can at best achieve the code coverage of 2 millions mutations from vanilla AFL. This can explains why the RNN-based fuzzer achieves 2 times new edges of AFL on some programs. If AFL gets stuck on 2 million mutations, RNN-based fuzzer would also get stuck on 1 million filtered mutations. However, NEUZZ is still capable of finding new code on 6 hours baseline.

Further, the RNN-based model has on average 16 more times training overhead than NEUZZ, because RNN models are not as efficient as CNN models in GPU training. The reason why NEUZZ outperforms the RNN-based fuzzer is that we obtain critical locations indirectly from the hidden layer of neural network by computing gradients, while the RNN model hardcodes all the critical locations manually in the training data and the model simply memorizes them. Our CNN model can also distinguish different contributing factors of critical bytes while the RNN model would treat them equally. As for mutation generation, we perform a tiered, exhaustive search for critical bytes determined by corresponding contributing factors, while the RNN-based fuzzer still relies on AFL's uniform random mutations.

Result 3: Neuzz, a CNN-based fuzzer, significantly outperforms the RNN-based fuzzer by achieving 1.5 to 126 times more edge coverage across different projects.

5 CASE STUDIES OF BUGS

There are four general types of bugs that NEUZZ finds which may lead to severe security vulnerability. Table 6 summarizes the total number of bugs found by running AFL and NEUZZ after generating 1M mutations, where NEUZZ consistently outperforms AFL in all programs.

In the following, we elaborate on three significant types of bugs discovered by NEUZZ: integer overflow, out-of-memory bug, and crash inducing, and illustrate the potential effects of these bugs.

⁷https://clang.llvm.org/docs/UndefinedBehaviorSanitizer.html

Table 7: Edge coverage comparison of NEUZZ (CNN fuzzer) and RNN fuzzer on 1M mutations

Programs	1 hc	our corpu	IS	6 hour corpus		
	NEUZZ	RNN	AFL	NEUZZ	RNN	AFL
readelf -a	2,378	215	213	2,451	131	4
libjpeg	142	21	28	126	1	0
libxml	273	38	19	133	15	0
mupdf	121	70	32	63	0	0

```
binutils -2.30/bfd/elf.c:6499
 #define IS_CONTAINED(section_addr, segment_size, base_addr) \
   (section_addr >= base_addr
     && section_addr <= (base_addr + segment_size))
  static bfd boolean
6 rewrite_elf_program_header (bfd *ibfd, bfd *obfd)
    do
      for(j = 0; j < section\_count; j++)
        section = sections[i];
        if (section == NULL)
          continue;
               section = section -> output_section ;
        if (IS_CONTAINED(output_section, segment_size, base_addr))
          isec++;
          sections[j] = NULL;
    } while (isec < section count);</pre>
```

Listing 2: strip integer overflow

We note that a large number of program bugs result from incorrect handling of extreme values of variables. As NEUZZ can enumerate all critical bytes from 0×00 to $0 \times \text{ff}$ (see Algorithm 1 line 3), such a strategy helps us to find all three types of bugs. For example, NEUZZ is able to find many out-of-memory bugs in libjpeg, objdump, nm and strip by setting the input bytes that affect memory allocation size to extremely large values.

strip's integer overflow. strip is a common ELF minimizer tool from Linux Binutils. It removes inessential information (*e.g.*, debug flag, program symbol tables) from the input file and create a new output file with smaller storage size for faster execution speed. NEUZZ finds an integer overflow bug that can induce an infinite loop on strip.

List 2 shows a function in the strip program that parses every section in the program header table of an input ELF file and assigns them to a new program header table in the output ELF file. When a section in the input file is successfully assigned to the corresponding memory segment in the output file, the counter variable isec is incremented by 1, and the section pointer is set to *NULL*. The outer while loop will run until all sections in the input file are assigned to a memory segment in the output file. The integer overflow occurs at the if-condition in line 17 where IS_CONTAINED(output_section, segment_size, base_addr) checks if output_section is in the range of the

```
1 // libjpeg/jmemmgr.c:444
2 (JBLOCKARRAY) alloc_barray (j_common_ptr cinfo, ...)
3 {
4 ...
5 while (currow < numrows) {
6 ...
7 alloc_large((size_t) rowsperchunk * (size_t) blocksperrow * SIZEOF(JBLOCK));
8 ...
9 }
10 }
```

Listing 3: libjpeg out-of-memory bug

segment. However, segment_size can be manipulated to be extremely large by malicious inputs generated from NEUZZ and result in an integer overflow when computing the end address for the segment base_addr + segment_size. Consequently, the end address of the segment would become smaller than the start address of the segment and if-condition in line 17 would never be satisfied. When the increment operation on the counter isec in line 20 for the outer while loop hides in the if-conditions in line 17, the counter isec would never be changed and cause an infinite loop.

<code>segment_size</code> is parsed from the field <code>p_filesz</code> in the program header of an ELF binary. Therefore, training data for <code>NEUZZ</code> containing ELF binaries with different values of <code>p_filesz</code> will have different edge coverage. Based on the diverse training set, <code>NEUZZ</code> can learn the bytes that determine the value of <code>p_filesz</code> as critical bytes, and the exhaustive search can find this integer overflow bug that causes the infinite loop. We find this bug in the latest version of <code>Binutils</code> and also discover the same bug in the older version of <code>strip-2.26</code> that comes with popular Linux distribution Ubuntu 16.04 and <code>strip-2.29</code>, which is bundled with Arch.

libjpeg's out-of-memory. JPEG is a commonly used format for lossy compression and storage of digital images. The JPEG file represents every color space as a component, and each component maintains a horizontal and vertical sampling factor. In th compression process, the data of every color space is downsampled by the corresponding sampling factor in order to reduce file size. In the decompression process, the original color space is restored by the same sampling factor. According to the JPEG standard, the sampling factor must be an integer between 1 and 4. The training data for NEUZZ consists of JPEG pictures with different valid sampling factors and corresponding different edge coverage. NEUZZ can learn the byte that determines the sampling factors in a JPEG file as a critical byte. Then it can enumerate all byte values in the mutation. As a result, the sampling factor can become an extremely large value not between 1 and 4, and the restored data size becomes extremely large correspondingly. As shown in List 3, libjpeg allocates memory buffers for incoming data of restored color space, the buffer size is determined by restored data size blocksperrow and numrows. These two variables are computed from sampling factor and are extremely large in our case. In our experiment, each alloc_large call would try to allocate 10GB memory, and all available memory is quickly drained up by libjpeg's huge memory consumption. Consequently, on a system without strict memory limitation for the process, the system would freeze instantly because of the out-ofmemory issue; on a system with proper memory restriction for the running process, libjpeg would be killed and cause a denial-ofservice to the tasks depending on libjpeg.

Listing 4: readelf section header parsing bug

readelf's crash. readelf is a ELF parser from Linux Binutils. It parses ELF file information stored in the program header and prints it out. Although the functionality of readelf seems trivial, the actual implementation code is very large and complex, including many corner cases. The main file for readelf has more than 19,000 lines of C code. An ELF file consists of a file header, program header, section header and section data. According to the ELF specification, the ELF header contains the field e_shnum located at the 60th byte for a 64 bit binary, which specifies the number of sections in the ELF file. The training data of NEUZZ contains ELF files with varying numbers of sections. Different sections trigger different parsing conditions of readelf. Thus NEUZZ can learn that 60th byte for ELF file is potentially a critical byte. In List 4, readelf parses the section header by checking the number of sections in the section header. If the number of sections is equal to 0, it returns NULL pointer to section header. The section header will be accessed by the following code and trigger an error assertion and cause a crash. NEUZZ can efficiently locate the byte that determines the field e_shnum as critical byte and mutate to 0 to expose this bug.

6 RELATED WORK

Learning-based fuzzing. Learning-based fuzzers aim to learn from a large number of past fuzzing samples and guide mutation with the learned model. These all require modeling all or part of the program logic into a learning problem, engineering the appropriate input-output representation of the collected data, and leveraging the learned models' capability to generalize to guide the mutation or generated test inputs to find bugs. Depending on the learning models, these include works on learning recurrent neural nets, namely RNNs/L-STMs/Seq2Seq [10, 29], probabilistic context-sensitive grammars (PCFGs) [37], synthesized context-free grammars (CFGs) [2], deterministic finite automaton (DFA) [35], deep reinforcement Q-learning [4], and generative adversarial nets (GANs) [27].

All of these different choices of learning algorithms are justified in each work according to the problem-specific tasks, where there is not any ad-hoc modeling show a distinct advantage over the others in every task. While we also leverage specific modeling in our problem-setting (*i.e.*, convolutional neural net) due to its efficiency in training and gradient computation, our work starts from a more

high-level point of view by noting the importance and power of neural program's differentiability in efficiently solving combinatorial bug-finding problems by gradient descent. On the other hand, our work also demonstrates the outperformance of differentiable neural programs in the effectiveness of guiding mutation over less principled evolutionary strategies [41].

Taint-based fuzzing. Taint analysis can track critical bytes in the input that affect the actual control flow of program execution. Such information can be extremely useful to guide the mutation when random fuzzing gets stuck. TaintScope [38] can identity security-sensitive bytes that affects system call and library call and focus on mutating these bytes. Dowser [13] targets buffer boundary violations. It uses taint analysis to locate the input bytes that influence the array index, and then uses symbolic execution on these bytes to explore the potential vulnerability. BORG [26] performs similar techniques to target buffer over-read vulnerability. It selects buffer accesses that could lead to an over-read and then guides symbolic execution towards those accesses. Vuzzer [30] and Steelix [21] infer magic bytes by static analysis and obtain the corresponding magic locations by taint analysis, then insert magic bytes to the input to generate mutations.

Angora [7], among other techniques, uses gradient descent on unmodified functions in a blackbox fashion. Due to the inherent of discontinuities of real-world function behaviors, such an approach is fundamentally limited and often gets stuck at plateaus. By contrast, NEUZZ leverages neural networks to smoothly approximate the program behaviors and bypass such issues.

Dynamic taint analysis relies on heavyweight program analysis techniques with nontrivial instrumentation overheads. On the contrary, NEUZZ learns critical byte locations in input from NN without any expensive program analysis techniques.

Symbolic/Concolic execution. Symbolic execution [17] represent predicates in the program as a set of constraints in the first-order logic formula, then solve these constraints by calling a solver to obtain the input that can trigger certain branch/path. It has been used by several tools to increase code coverage and find bugs [5, 8, 24, 33]. SAGE [9] uses symbolic execution to generate inputs that can trigger desired program state in fuzzing. SYMFUZZ [6] leverages symbolic execution on a given program-seed pair to detect dependencies among the bit positions of the input, then use the dependencies information to compute the optimal mutation rate. Driller [36] combines fuzzing with selective concolic execution in a complementary manner. It uses concolic execution to generate input when the fuzzer gets stuck. However, all of these tools struggle scale to larger programs due to,e.g.,, path explosion or some hard constraints that the underlying solver cannot easily solve. NEUZZ does not rely on any heavy program anlysis techniques like symbolic execution and can freely scale to large programs.

7 CONCLUSION

We presented NEUZZ, an efficient learning-enabled fuzzer that uses a differentiable surrogate neural program to closely approximate a target program. We further demonstrated how new test inputs that trigger new control flow edges can be efficiently generated by performing gradient descent on the differentiable neural program. NEUZZ significantly outperformed the state-of-the-art fuzzer AFL both in edge coverage and numbers of detected bugs: it found 36 previously unknown bugs that AFL failed to find in 10 popular real-world programs. NEUZZ also achieved 9× more edge coverage while taking 16× less training time than other neural-network-based fuzzers [29]. Our work showcases a successful application of neural program learning to approximate the discrete program logic for efficient fuzzing. We believe our results demonstrate the vast potential of leveraging differentiable neural program learning to perform scalable approximate program analysis for security testing, debugging, etc. We hope our work will encourage more researchers to explore such directions.

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